Jack of all Trades:

Can Artificial Intelligence Revolutionize International Trade?

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Abstract

In a time where warning and legislation are intertwined with the continuous democratization of AI, the future of trade stands at a crossroad. Thus, we set our eyes on the implication of this disruptive technology on international trade. Specifically, this research considers how the studied microeconomic effects of AI on topics such as productivity can be translated to the macroeconomic world of trade. In order to solve this problematic, the paper shapes the renowned gravity model into a theoretical and empirical framework, through the combination of multiple theories. This analysis allowed us to conclude that the results do not point towards a single consensus regarding the impact of AI. Indeed, we find that while AI usage reduces both bilateral trade volumes and the negative impact of non-tariff barriers on these transactions, it has a positive effect on the number of exporters in a country.

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1. Introduction

Since the post Covid era, fiction has become reality with the prominent rise of Artificial Intelligence (AI), raising concerns and sparking interest across the globe. Recognizing the urgent need to address these developments, on March 13, 2024, following three years of extensive deliberation, the European Parliament adopted the first comprehensive AI legislation. This law focuses on safeguarding fundamental rights, upholding democracy, ensuring the rule of law, and promoting environmental sustainability (European Parliament, 2024). Though groundbreaking, this legislation is merely the first step in a series of essential changes needed to ensure humanity's control over this technology. Indeed, AI has already demonstrated its remarkable efficiency in revolutionizing the microeconomic aspect of industries by transforming individual business operations and consumer interactions. Through advanced data analytics, machine learning, and automation, AI enables businesses to optimize their production processes, reduce costs, and enhance consumer experience. For instance, AI-driven predictive maintenance systems help manufacturers anticipate equipment failures, thereby minimizing downtime and extending machinery lifespan (Biz Technology Solutions, 2024). In retail, personalized AI algorithms analyze consumer behavior to tailor marketing strategies and improve customer experiences, leading to increased sales and customer loyalty (Babatunde et al., 2024). Moreover, AI-powered financial technologies, such as robo-advisors, have facilitated access to investment advice and streamlined financial transactions, making financial markets more efficient (Roh, Park & Xiao, 2023). By automating routine tasks and providing educated insights, AI has empowered businesses to make data-driven decisions, fostering innovation and competitiveness at the microeconomic level.

While the impact of AI on microeconomic processes has been apparent, it is clear that its macroeconomic counterpart has so far been overlooked by researchers. As we have come to see, AI has gradually revolutionized most industries and domains of society, the world of trading being no exception. Evidently, if a firm has access to this new technology, providing enhanced manufacturing processes and services, it seems fair to assume that it will not solely impact its own country’s economy. The integration of AI into international trade promises to optimize supply chain management, improve logistics, and enhance decision-making through predictive analytics (Meltzer, 2018). For instance, while suppliers and buyers can easily connect through the internet, a trained AI could directly build an optimized supply chain for any business. This could increase both the intensive and extensive margins of trade (Ahn et al., 2011) by facilitating trade for exporters, while reducing the fixed costs of new international players. Besides these beneficial effects, AI applications could also hinder trade flows by ensuring a better enforcement of product standards and better control of counterfeit goods and patent protection. For example, if all producers and goods were recorded in the blockchain, it would be difficult to pass an AI border control with an unapproved product (Burri, 2021).

Thus, this research's main goal is to investigate some of the uncertainties brought by this new technology by answering the following research question:

What is the impact of Artificial Intelligence technologies on international trade flows?

In order to thoroughly answer the overarching research question, and propose a relevant contribution to the topic, we investigate three hypotheses:

1. *AI technologies have the ability to enhance trade volumes by facilitating transactions and make them more effective.*

2. *AI technologies negatively impact trade flows by enhancing the enforcement of trade barriers such as product standards.*

3. *AI technologies increase the extensive margin of trade by making exporting more accessible*

To achieve our goal, we compile data on the trade flows, macroeconomic indicators and AI technologies of the European Union 27 member states . First, we theoretically expand the famous gravity model and Melitz-Chaney (2008) framework to allow for AI technologies. In this manner, we construct a base framework that incorporates arguments from available literature and which provides a foundation to investigate an issue that is not rich in data. Then, we empirically test the three resulting hypotheses by incorporating the data into two linear regressions based on these log-linearized augmented models.

This allows us to demonstrate that only hypothesis three is supported by the data. Indeed, our results concerning hypothesis 1 show that the use of AI technologies is associated with a decrease, instead of an increase, in the volume of bilateral trade flows for a country pair. Similarly, for hypothesis 2, contrary to an expected reduction in trade flows due to better enforcement, we observe that an increase of AI usage is linked to a reduction of the negative impact of non-tariff barriers on bilateral trade flows. Nevertheless, the analysis proved that hypothesis 3 holds as we find that an increase in ICT equipment, serving as a proxy for AI, correlates with an increase in the number of exporting firms in a country.

The remainder of this paper will be structured as follows. First, the societal relevance of this research will be addressed, followed by its scientific relevance in the form of a literature review which contextualizes the paper in the existing literature. In the methodology section, we build both our theoretical and empirical models. Continuing with the data section, we bring detailed information on the data source, variables and the justification for our specific choices. The result section allows us to investigate the robustness of the empirical models and display our findings. Finally, before concluding, we dive into the discussion to evaluate the validity of the main findings, potential explanations for their deviation from our hypotheses, and possible directions for future research.

2. Societal relevance

The relevance of studying the emergence of AI in international trade lies in understanding a new world of technology that will most likely revolutionize a great number of industries. Understanding its nuances and complexities is thus crucial to ensure a smooth transition into this new technological era.

Firstly, it allows a better understanding of the potential of AI to enhance regulatory enforcement and fairness in international trade, which can address significant economic and social issues. A current example can be found in the claim of French farmers, who argue that they are competing with illegally imported products, as these do not follow European standards (France Bleu, 2024). If AI is indeed considered able to enforce standards at borders more effectively, it could reduce the number of such complaints and facilitate transition to standards with positive externalities that might otherwise be discarded due to competitiveness issues. Moreover, by ensuring that all market participants adhere to the same standards, AI-driven regulatory enforcement could promote economic and social equity to prevent the undercutting of domestic industries by non-compliant imports, which would be crucial for maintaining fair competition and equitable economic opportunities. Overall, this could contribute to a more balanced and fair international trade environment, where all players can compete on equal terms, benefiting society as a whole.

Secondly, the evolution of AI and its integration into various sectors has the potential to significantly impact unemployment and labor displacement internationally. New AI technological advancement can lead to job displacement in sectors where tasks are repetitive or routine, such as logistics, warehousing, and manufacturing (Talmage-Rostron, 2024). This can result in economic instability as workers face unemployment and struggle to find new job opportunities. However, understanding these impacts allows for the development of targeted reskilling and upskilling programs that help displaced workers transition into new roles. AI can also create new job opportunities in tech-driven sectors, enhancing productivity and innovation. For instance, AI specialists, data analysts, and robotics engineers are increasingly in demand. By equipping the workforce with the necessary skills, we can ensure that the transition to an AI-driven economy is inclusive and beneficial to all. Moreover, comprehending the dynamics of labor displacement and job creation helps in formulating social safety nets and support systems to assist workers during the transition period, thus promoting social stability and cohesion (Tiwari R. (2023).

Finally, the research is highly relevant due to the urgency of scientifically informing policy makers on the implications of AI in trade as, due to the novel nature of the topic, it is currently significantly under-researched. For instance, AI's role in international trade brings new challenges and opportunities related to intellectual property rights. Thus, by establishing clear guidelines and regulations for AI-generated content and inventions, policymakers can foster innovation while safeguarding intellectual property (Jones, 2023). This protection is vital for encouraging technological advancement and ensuring that creators receive fair compensation for their work. Therefore, building a comprehensive framework evaluating the benefits and costs of AI usage is essential to harness AI's potential while mitigating its risks. Such a framework ensures that AI's integration into trade is beneficial for society, balancing technological progress with economic and social well-being.

In conclusion, studying the emergence of AI in international trade is crucial for understanding and navigating the profound changes it brings. By addressing regulatory, economic, social, and policy implications, we can ensure a more equitable, stable, and innovative global trade environment that benefits society as a whole.

3. Literature Review

Having discussed the societal relevance of the research, it is now necessary to turn our gaze to the scientific contribution of this paper by placing it in the context of existing literature.

As previously mentioned, the current focus of the prevailing literature is to assess the effect of AI technologies on micro aspects of the economy. Yang (2022) explores AI' impacts on the productivity and employment of Taiwanese firms. He observes that AI enhances productivity and either increases employment for firms creating the AI tools, or has a labor substitution effect in the manufacturing sector. Following up on productivity implications, Noy and Zhang (2023) find that AI chatbots affect the performance of workers in mid-level professional writing tasks. Through a randomization experiment, they uncover positive effects on both rapidity and quality of the work produced. Acemoglu and Restrep (2018), find similar results as they provide proof of productivity enhanced by AI technologies, however, they also observe risks of interference with productivity through excessive automation and labor skill shortages. Moreover, the authors discuss employment, noting that despite initial worker displacements, countervailing effects such as the creation of new industries can help reduce these displacements if labor has a comparative advantage over capital.

Having laid the microeconomic foundations of AI, we now have the necessary background to explore their implications in the macroeconomic sphere, more specifically trade. Marriaga and Bonfante (2023) focus on the multiple benefits that the blockchain can have for international trade. They describe how a large share of Latin American economies rely on small and medium enterprises (SMEs) who face inefficient processes in conducting their trade practices, especially regarding supply chain management. In light of this issue, the authors argue that the blockchain can help these companies by centralizing global stakeholders' information, bringing about a trustworthy platform, with less room for information asymmetries. In this situation, the paper states that Artificial Intelligence would help smooth out the process when coupled with the blockchain. Indeed, Charles, Emrouznejad and Gherman (2023) highlight that the blockchain, in its current state, can be challenging to adopt and implement in the supply chain networks. However, they argue that AI can be used to automate the extraction of valuable information and perform the necessary analysis to improve supply chains without the need for intermediaries. A 2018 report from the World Trade Organization further ascertains this point by supporting the ideas that the blockchain can help form trustworthy and transparent supply chains, reduce a substantial range of trade costs and create opportunities for SMEs. The report states that AI is a necessary anchor for this innovation, as the blockchain will only be able to live up to these expectations, if the data can be processed by all the concerned parties. Moreover, AI is not only capable of enhancing digital processes, but also physical transports, such as in the domain of shipping (Lambrou, Watanabe & Lida, 2019). According to this paper, AI fleet planning and energy consumption monitoring could, among other things, be coupled with 'smart' vessels to render the process more time and cost effective.

Finally, we notice a gap in literature regarding how AI can negatively impact 'growth', or more specifically for our area of research, how AI might impact the development of trade flows. Indeed, there have been reports on how AI can be used alongside blockchain and big data technologies at customs controls, in order to enforce product standards and control for counterfeit or illegal goods (Burri, 2021). For instance, AI computer vision, natural language processing, and predictive modeling can be applied to improve the efficiency and accuracy of customs operations. This also applies to how the Internet of Things compiles large amounts of information on the origin of goods and their production, to increase traceability. Moreover, similar uses of AI have also been documented in the domain of finance for fraud detection (Goodell, 2021). For example, Fukas et al. (2022) describe how an AI can be trained on a dataset of fraudulent firms to effectively predict and detect future fraud. While these instances appear to provide positive externalities to society, they can equally be the source of degrading trade (equity in finance) flows, an omitted impact in these publications. An example of that can be seen when investigating stricter product standards, which can be assimilated to harsher border controls. Shepherd (2015) demonstrates that, while internationally harmonized standards may increase exports variety for high income countries that can easily adapt, they are associated with a decrease in exports variety for low income countries. Ferro, Otsuki and Wilson (2015) further develop this argument by stating that low-income countries will be particularly affected due to their lack of resources to adapt. Furthermore, they relate stricter standards to higher fixed costs that, once covered, will mitigate the negative effect. They argue that this theory is reflected by the close to null effect in the data when controlled for sample selection and exporting firms, which proves the discrepancy of the impact depending on the exporter's origin.

Therefore, our scientific contribution consists of applying the existing and developed micro literature regarding AI impact on efficiency to model the more limited application of AI on macroeconomics, and more specifically, trade. We also explore the less documented and favored hypothesis that the use of this disruptive technology might negatively impact the intensive margin of trade.

4. Methodology

4.1 The Models

In order to provide a rigorous analysis of the impact of AI on international trade, we must adapt our method to the novelty of AI related questions and the scarcity of data it implies. Thus, we first develop a theoretical approach to the problem, by adapting two renowned models in international economics, the Tinbergen gravity equation and the Melitz-Chaney (2008) open-economy with heterogeneous firms model, extended through Ahn et al. (2011).

We start with the classical gravity equation (1) and expand the model to capture how variations related to AI impact our different hypotheses. The gravity model is known to provide reliable estimates of bilateral flows between two countries, i and j, based on the product of their Gross Domestic Products (GDP) and the distance that separate them. Indeed, a regression of the linearized equation tends to yield coefficients close to 1 for the GDPs and -1 for the distance (Krugman, Obstfeld, & Melitz, 2020).

$$T_{ij,t} = \frac{GDP_{i,t} * GDP_{j,t}}{D_{ij}} \quad (1)$$

Due to these characteristics, the model has been used to explain the impact of different economic variables on trade, such as the advent of technology and automation in manufacturing (Chai & Wang, 2023). From a different perspective, Portes and Rey (2005) revise the gravity equation and show that it is as performant to explain cross-border equity flows, than goods trade. Tinbergen's model has also been adapted to disciplines that have limited correlation with economics and finance such as medicine (Stein & Rohrich, 2023). Thanks to this versatility and a history of acclimating well to different areas of research, we deem the gravity equation to be the most suitable candidate for an analysis regarding a quantitative shift in trade volumes.

Our first hypothesis is that AI technologies have the ability to enhance trade volumes by facilitating transactions, making them more effective. Thus, this effect is related to the intensive margin of trade and how exporters and importers are increasing their transaction volumes with the help of AI. This statement tends to revolve around AI being paired with the blockchain technology to read and analyze information and propose effective solutions to firms (Marriaga & Bonfante, 2023). For example, a large share of recent trade history has been in intermediate output through offshoring and international supply chains. These transactions are victims of multiple frictions such as language and knowledge of foreign markets, which could be relaxed by the introduction of AI (Portes & Rey, 2005). Considering that both upstream and downstream businesses can be encoded in the blockchain with their characteristics and offers, a firm with access to AI could use this tool to objectively build the most efficient supply chain based on its needs (Marriaga & Bonfante, 2023). The assumption is that this should increase trade flows, as more financial resources could be allocated to these transactions, rather than on constructing them. Thus, we add a group of trade enhancing AI variables $Enhancing_{ij,t}$ on the numerator in equation (2).

For our second hypothesis, we model how AI technologies could negatively impact trade flows as mentioned in the literature review. The work of Burri (2021) provides a strong basis to support our claim that AI might be capable of enhancing the enforcement of trade barriers, such as product standards. As a result, we extend the gravity equation (2) by including a new term, $Impediments_{ij,t}$, at the denominator. This yields the following equation:

$$T_{ij,t} = \frac{GDP_{i,t} * GDP_{j,t} * Enhancing_{ij,t}}{D_{ij} * Impediments_{ij,t}} \quad (2)$$

Finally, our third hypothesis makes use of the Melitz-Chaney (2008) model and investigates the benefits of AI use towards the extensive margin of trade. The main intuition is derived from the work of Ahn et al. (2011) who discusses the role of intermediaries in trade. In their paper, the authors argue that the productivity cutoff for exporters can be lowered through cooperation with intermediaries. Indeed, these intermediate firms provide facilitating services that lower the fixed cost of exporting, in exchange of a subscription fee. Therefore, their existence enables less productive firms to take part in international markets, when they could not afford to on their own. We consider that AI technologies, taking the role of a personal digital assistant and manager, can provide a similar help to businesses. For instance, a firm that could not afford the cost of research and planning to match with trade partners could rely on AI and their relatively affordable cost to build this supply chain (Atkinson, 2024).

The productivity cutoff, $\bar{\varphi}_{ij}$, in Melitz-Chaney (2008) is represented by equation (3) where the last term symbolizes the fixed costs of exporting from i to j:

$$\bar{\varphi}_{\mathrm{ij}} = \left(\frac{\sigma}{(\mu\,(L_{\mathrm{j}} + \Pi/2)}\,\frac{\gamma}{(\gamma - (\sigma - 1)}\right)^{\frac{1}{\gamma}} * \left(\frac{\tau_{\mathrm{ij}}}{\theta_{\mathrm{j}}}\right) * F_{\mathrm{ij}}^{\frac{1}{(\sigma - 1)}} \quad (3)$$

The classical assumption that the elasticity of substitution between varieties σ is larger than 1, allows us to apply the following modification. Anh et al. (2011) consider that intermediary firms, in our study: AI technologies, reduce the fixed cost of exporting. Therefore, we rewrite Fij as a decreasing function of AI.

$$F_{ij}(AI) \text{ with } \frac{\partial F_{ij}}{\partial AI} < 0 \quad (4)$$

4.2 The empirical evaluation

In order to find empirical evidence for our models' findings we run a set of regressions to investigate each hypothesis. For the first two, we proceed with a standard log linearization of the gravity model they are based on. This yields the following equation:

$$\ln\left(T_{ij,t}\right) = \beta_0 + \beta_1 \ln\left(GDP_{i,t}\right) + \beta_2 \ln\left(GDP_{j,t}\right) + \beta_3 \ln\left(Enhancing_{ij,t}\right) + \beta_4 \ln\left(D_{ij}\right) +$$

$$\beta_5\left(Impediments_{ij,t}\right) + Time\ Dummies + Geographic\ Dummies\ \varepsilon_{ij,t} \quad (5)$$

On the one hand, β_3, which we predict to be positive, captures the positive effects of the first hypotheses. On the other hand, we predict a negative coefficient for β_5, as it evaluates the negative effects attributed to the second hypothesis' variables. β_1 and β_2 should, according to the above theory, be positive and close to 1, while β_4 should be of the same amplitude but negative. All variables are defined with respect to the source (i) and partner (j) countries, forming pair (ij), for a certain time (t) at the exception of the distance D_{ij} which is, by nature, time invariable. The vector $Enhancing_{ij,t}$ comprises of the variable $AI\ Source_{ij,t}$ and $AI\ Partner_{ij,t}$ defined in the Data section while $Impediments_{ij,t}$ consists of the variable $TBI_{ij,t}$. To run this regression, we use solely the years 2021 and 2023 of the sample as it is the timeframe for which the variable $AI\ Source_{ij,t}$ and $AI\ Partner_{ij,t}$ are available.

Regarding the third hypothesis and the effect of AI technologies on the productivity cutoff for exporter, we proceed in the fashion of Bernard, Jensen, Redding and Schott (2007) who adapt another gravity equation to evaluate the question of the extensive trade margin:

$$\ln\left(Number\ of\ firms_{i,t}\right) = \beta_0 + \beta_1 \ln\left(GDP_{i,t}\right) + \beta_2 \ln\left(GDP_{j,t}\right) + \beta_3 \ln\left(AITech_{i,t}\right) + \beta_4 \ln\left(D_{ij}\right) + Time\ Dummies + Geographic\ Dummies \varepsilon_{ij,t} \quad (6)$$

This regression displays the number of exporting firms in a home country (i) at time (t) as a function of the exporter's (i) and importer's (j) GDP, the distance between the pair and our variable of interest $AITech_{i,t}$, a vector that consists of $ICT\ Source_{ij,t}$ and $ICT\ Partner_{ij,t}$. We expect the latter's coefficient, β_3, to be positive as a lower theorized productivity threshold due to AI should increase the number of exporters. β_1, β_2 should remain positive, while β_4 should, equally, stay negative. However, we do not expect a significant result for β_1 as $Number\ of\ firms_{i,t}$ includes only exporters and should be less correlated to the domestic market. This time the regression uses the years 2021 and 2022 as $Number\ of\ firms_{i,t}$ has yet to be recorded for 2023. Due to this limitation, we also had to change the explanatory variables with $ICT\ Source_{ij,t}$ and $ICT\ Partner_{ij,t}$, since $AI\ Source_{ij,t}$ and $AI\ Partner_{ij,t}$ are not reported in 2022. We consider this proxy to be less precise but still reliable as ICT equipment is required to access AI technologies. Finally, both models include time dummies, as well as geographic dummies to control for country or country-pair variables.

5. Data

For the conception of this paper, we use the European Union (EU) and its 27 members as our region of reference. Our intuition for this choice is that, by choosing to analyze trade within the EU's single market and custom union, we make abstraction of many variable discrepancies that could impact our analysis. The best database candidate in this context is Eurostat (2024) which regroups a large panel of country and industry data. More specifically, we collect this information for the year range 2021-2023. This decision is, on the one hand, motivated by data limitation, as we desired to use information collected by Eurostat on the use of AI by firms which only started to be collected in 2021 on a biannual basis. On the other hand, we consider this to be the most relevant period to study AI technologies as this post-covid period provides the largest interest and access to the public. We consider two time indicators to justify this statement. First, the release of ChatGPT between June 2020 and November 2022 with the 'developers only' version preceding the public access. Second, the Google Trends (2024) chart for the term 'Artificial Intelligence' which saw a sharp increase in the last 2 years (Appendix 9.2). With this process we retrieve data for the following variables:

- $Export_{ij}$: The value in euros of exported goods from countries i to j
- $Import_{ij}$: The value in euros of imported goods by countries i from j
- Bilateral $flows_{ij}$: The value in euros of the total trade transaction for a country pair ij that we arithmetically obtain from the two previous variables
- GDP_i : The gross domestic product in current prices - millions of euros for country i
- GDP_j : The gross domestic product in current prices - millions of euros for country j
- AI Source: The percentage of firms with 10 employees or more in country i that use the following AI technologies TTM, TSR, TNLG, TIR, TML, TPA, TAR (Appendix 9.2)
- AI Partner: The percentage of firms with 10 employees or more in country j that use the following AI technologies TTM, TSR, TNLG, TIR, TML, TPA, TAR (Appendix 9.2)
- Number of $firms_i$: Number of Intra-EU exporting firms in country i

- ICT Source: The stock of ICT equipment capital for industries in current prices - millions of euros in country i
- ICT Partner: The stock of ICT equipment capital for industries in current prices - millions of euros in country j

Besides Eurostat numbers, we collect data from two other sources. Based on the above list, we are missing information on the physical distance between the trading partners, to make a complete gravity model. Given the different arbitrary options available, we replicate the method of Portes and Rey (2005) and decide to base this variable on the distance between capital cities. We retrieve this information from Gleditsch's (2021) website which provides the great circle distance between capital cities in kilometers for every country. Finally, we gather data from the Tholos Foundation (2023) which created the International Trade Barrier Index (TBI) in 2019. We use this measure to approximate product standards in the model as it compiles a comprehensive source of different types of trade barriers (Appendix 9.2). Their method allows for discrepancies in every country's score even in our customs union context.

6. Results

Before diving into the results, we would like to state that our study does not have for objective to uncover causal effects. Given the recency and incompleteness of the data, we primarily wish to provide a predictive insight on the studied matter and a framework to approach the question. This result section thus serves as an empirical support for our models and displays solely association between the data.

6.1 Robustness

All the following figures mentioned will be displayed in Appendix (9.1). We first evaluate the robustness of the empirical specifications and their results through the classical assumptions of Ordinary Least Square regressions. Starting with the assumption of normality, we observe Figure (1) that displays the Q-Q plot of residuals for equation (5). There appears to be normality as the residuals follow the 45 degree line despite some slight deviations at both extremes. We perform a Shapiro–Wilk test to supplement our analytical findings and obtain a significant result. However, further tests show that skewness is normal, while kurtosis is the problematic component of the residuals' distribution. This measure is less of a threat to normality as it is highly influenced by sample size (Wheeler, 2004). However, as can be seen in Figure (2), normality might stand to concern in equation (6). The residuals do follow the 45 degree line, but some patterns can be observed once again at the tails and more slightly on the mean. Here the Shapiro–Wilk test is again significant, but this time with a significant skewness rather than kurtosis. This component of the residual can be problematic and should serve as caution for the accuracy of the results of equation 6.

To assess the linearity of residuals, we plot the fitted values against the residuals in Figure (3) and Figure (4) for equation (5) and (6) respectively. In Figure (3) the residuals appear to be linear as they are randomly distributed around the 0 line. Nonetheless, we stay aware of a slight decreasing trend on the far right, which could potentially point towards a concave shape. However, without a larger sample size, this non-normality cannot be assured to hold. For Figure (4), the residuals depict a negative linear slope instead of the usual distribution around 0. While the absence of a curvature reassures us on the omission of a non-linear component, it could point towards an issue of fit, possibly outlined by the non-significant intercept seen in the next section.

Regarding heteroscedasticity, the spread of the residuals is roughly equal for equation (5) in Figure (3), despite some narrowing on the right of the graph. A similar trend is underlined by Figure (4) for equation (6), with a smaller spread around the 0 line as we reach the end of the graph. In order to investigate potential serial correlations, we move to Figures (5) and (6) for equations (5) and (6) respectively. While we do not recognize problematic patterns, it is important to note that we are observing a short and recent time frame that might not show the whole picture for uncovering correlations in errors. This limitation also holds for empirical tests like a Breusch–Godfrey, that cannot take lags with only two time periods.

6.2 Empirical Results

As can be observed in Table 1, our first two hypotheses do not seem to hold empirically. In column 1, we notice that the gravity model appears to be robust to our dataset with both countries' GDPs and Distance being respectively close to 1 and -1 as well as significant at the 95% confidence level. Nevertheless, it can be noted that concerning distance, the difference is larger and thus appears to matter more for the European Union than their GDP. Regarding our main variables of interest, we use the coefficients from the third column. Indeed, while we gain some information by controlling for i and j, adding ij in column 4 and 5 is irrelevant and mainly modifies the intercept. This is probably due to the GDPs and Distance variables which capture most of the effect from these dummies. Following this insight, a 1% increase in $\ln\,(AI\ Source_{ij,t})$ is associated with 0.372% decrease in $\ln\,(Bilateralflow_{ij,t})$ at the 95% confidence level. Likewise, a 1% increase in $\ln\,(AI\ Partner_{ij,t})$ is associated with a 0.226% decrease in $\ln\,(Bilateralflow_{ij,t})$ at the 95% confidence level. As a result, hypothesis 1 does not hold as AI usage by firms in a country pair negatively impacts their trade volume.

In column 2, we try to evaluate the second hypothesis by including the TBI variable. GDPs and distance are not substantially different from column 2 and $\ln\,(Bilateralflow_{ij,t})$ coefficients even remain unchanged from the addition of $\ln\,(TBI_{ij,t})$. Nevertheless, for the same reasons as before, we retrieve our coefficients from column 3 with the additional controls information. As expected from the literature, a 1% increase in the TBI score is associated with a 1.093% decrease in $\ln\,(Bilateralflow_{ij,t})$ at the 95% confidence level. However, this addition did make $\ln(AI\ Soiurce_{ij,t})$'s coefficients 0.059 more negative without the controls and 0.055 with. This change uncovers a positive bias as the $\ln(AI\ Soiurce_{ij,t})$ effect was overestimated, or less negative than with the $\ln\,(TBI_{ij,t})$ control. Given that $\ln(AI\ Soiurce_{ij,t})$ is negatively correlated with $\ln\,(Bilateralflow_{ij,t})$, the only possibility for a positive bias is that $\ln(AI\ Soiurce_{ij,t})$ and $\ln\,(TBI_{ij,t})$ are negatively correlated as well. Therefore, contrary to the expectations of hypothesis 2, this means that a percentage increase in $\ln(AI\ Soiurce_{ij,t})$ decreases $\ln\,(TBI_{ij,t})$.

Finally, in Table 2 column 2, we explore our third and last hypothesis as we change the observed period and dependent variable. In this situation, the implications of the gravity model are less robust as $\ln\,(GDP_i)$ and the distance, despite being of the correct sign, are far from their theorized magnitudes. Moreover, (GDP_j) is close to 0 and non-significant, while we would have expected it to be relevant for a firm's choice to export in j. As for our variables of interest, only $\ln\left(ICT\ Source_{ij,t}\right)$ is significant at the 10% level. A 1% increase is associated with a 0.247% increase in $\ln\,(Numberoffirms_{ij,t})$ at the 95% confidence level which confirms our hypothesis.

Table 1: Regression of Bilateral trade flow on AI technologies in a gravity equation

	2021 & 2023				
	(1)	(2)	(3)	(4)	(5)
	lnBilateralflow	lnBilateralflow	lnBilateralflow	lnBilateralflow	lnBilateralflow
lnGDPSource	.952***	.93***	.928***	.929***	.928***
	(.014)	(.015)	(.015)	(.015)	(.015)
lnGDPPartner	.912***	.912***	.91***	.912***	.91***
	(.014)	(.014)	(.014)	(.014)	(.014)
lnDistance	-1.336***	-1.338***	-1.349***	-1.344***	-1.349***
	(.029)	(.029)	(.029)	(.029)	(.029)
lnAIsource	-.317***	-.376***	-.372***	-.371***	-.372***
	(.032)	(.037)	(.036)	(.037)	(.036)
lnAIpartner	-.226***	-.226***	-.223***	-.226***	-.223***
	(.032)	(.032)	(.032)	(.032)	(.032)
lnTBI		-1.127***	-1.093***	-1.09***	-1.093***
		(.337)	(.336)	(.337)	(.336)
Time	-.08**	.046	.043	.042	.043
	(.039)	(.054)	(.054)	(.054)	(.054)
Source i			.006**		-.822
			(.002)		(1.805)
Partner j			.007***		-.024
			(002)		(.067)
Pair ij				.000	.032
				(.000)	(.069)
_cons	6.119***	7.59***	7.522***	7.536***	8.365***
	(.371)	(.574)	(.573)	(.574)	(1.924)
Observations	1404	1404	1404	1404	1404
R-squared	.89	.891	.892	.892	0.891

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 2: Regression of Number of firms on ICT equipment (AI proxy) in a gravity equation

	2021 & 2022		
	(1) lnNumberoffirms	(2) lnNumberoffirms	(3) lnNumberoffirms
lnGDPi	.718***	.635***	.635***
	(.087)	(.085)	(.085)
lnGDPj	.005	.007	.007
	(.063)	(.061)	(.061)
lnDistanceij	-.168***	-.192***	-.192***
	(.046)	(.045)	(.045)
lnICTSource	.155*	.247***	.247***
	(.088)	(.086)	(.086)
lnICTPartner	-.01	-.013	-.013
	(.059)	(.057)	(.057)
Time	-.149*	-.11	-.11
	(.078)	(.076)	(.076)
Source i		.031***	-.8***
		(.004)	(.2.859)
Partner j		.001	-.029
		(.004)	(.106)
Pair ij			.032
			(.11)
_cons	1.126	1.144	1.989
	(.699)	(.678)	(2.984)
Observations	807	807	807
R-squared	.678	.7	.7

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

7. Discussion

7.1 Validity

Before discussing the results, it is important to evaluate the validity of the statistical study. Firstly, we do not consider the model to be sensitive to outliers. If at all, extreme points consistent across all variables could reveal interesting insight for the results. However, a model with logarithmic estimators is known to be especially susceptible to a large number of zeros. In that respect, our model is also deprived of any zero observation points.

Secondly, it appears safe to assume that the results are internally valid. This assumption relies on the above section and the fact that we have gathered data for the whole region of interest and obtained up to 27x26x2 = 1404 observation points (Portes & Rey, 2005). However, we notice some missing data concerning equation 6, which might explain our concerns about the accuracy of the results underlined by the robustness evaluation.

Lastly, concerning the external validity, the discussion appears more nuanced. While the time period seems to be the most suitable to conduct the study for it to be replicable, the region and variables display less certainty. On the one hand, the EU is always a complicated region to argue for external validity in trade with its unique customs union and single market. On the other hand, given that we are using proxy variables, there might be a large variability between our measures and the ones from other studies. Furthermore, as AI technologies continue to grow and develop across the globe, it raises concern for the relevance of our study in the foreseeable future.

7.2 Findings

Besides uncovering results that contradict our theoretical hypotheses, the most striking aspect of these findings is the paradoxical implications they entail. Indeed, considering that hypothesis 3 holds while hypothesis 1 does not, it brings to light an increasing extensive margin of trade with a simultaneous decrease in intensive margin.

Even though this conclusion appears contradictory at first, a number of factors could explain this phenomenon. Indeed, as previously mentioned, AI technologies could have the ability to facilitate trade and supply chain by catering to companies' needs and characteristics. However, this might not necessarily increase trade flows, as we first predicted, if international transactions would become more 'precise'. To illustrate this precision component, consider that a firm acquires the necessary AI technologies to benefit from our theorized trade benefits. It now has the ability to find the best product match in terms of quality and performance for its supply chain provisions. This entails that management will no longer have to discard non-conforming products, as they are able to obtain the best match directly, regardless of past information asymmetries. Ultimately, this would decrease unnecessary re-orders, artificially boosting trade flows as the best product is now obtained from the start. Moreover, production processes might become more efficient due to those improved inputs leading to less orders by downstream firms to satisfy their production needs. Lastly, the possibility to look for the most fitting product could open doors to more specialization and niche production for new firms, by enabling them to connect with buyers more easily. As a result, this scenario highlights how this novel component might allow for new companies to enter the export market, while current exporters might face a reduction in trade flows, in favor of better quality transactions.

Another possibility to explain these contradictory findings, relies on property rights and replication issues. As we have already discussed, policy makers are concerned about property rights infringement when AI replicates existing production processes (Chesterman, 2024). The same holds true for applying those rights to digital creations using AI technologies. Going back to our fictional firm, while it had been importing certain inputs in the past, AI technologies might now be able to replicate the production processes domestically at a lower cost than trading. This effect can be especially expected for trade in digital creation services such as art or music. While this outcome should follow the recent reshoring trend, it will depend on the legislative framework and might proliferate less in regions like the EU, where an AI act is now in force (Morello, Patrucco & Harland, 2020).

Finally, we turn our attention to hypothesis 2 and explore the possible reasons for its rejection. Part of the literature we have covered, relates product standards and similar non-tariff barriers to a type of fixed costs (Ferro, Otsuki, & Wilson, 2015). Therefore, AI technologies, making circumvention of these barriers more difficult, can be assimilated to an additional fixed cost for firms. The decreased chance of circumvention could, in turn, incentivize adoption of these standards by foreign firms and thus enhance bilateral trade flows instead of reducing them. Nonetheless, the literature also highlights the discrepancy between developed and developing countries for adopting these standards. The latter would face harsher consequences after an AI enhancement of border controls, possibly adding an argument against external validity of our study. Indeed, when observing trade vis-à-vis developing countries, our second hypothesis could now hold at least in the short term.

7.3 Proposal for further studies

The young nature of this research field leaves a large panel of possible future studies and enhancement to evaluate the incidence of AI on trade development. Some of our suggestions include the use of more comprehensive variables than proxies, which should gradually become more available as the technology spreads worldwide. Moreover, with the democratization of AI, we expect the gathered data to be of better quality and precision, which could reveal new insights and patterns in the future. More importantly, we emphasize the need to evaluate the impact of AI on trade for multiple regions and specifically developing countries when these data will become accessible. Finally, we suggest studying the impact of AI on other international flows, such as with cross-border equity flows in the domain of finance (Portes & Rey, 2005).

8. Conclusion

This paper examines the impact of AI technologies on international flows by evaluating both the extensive and intensive margins of trade, as well as the implications for non-tariff barriers. To perform an analysis of the recent phenomenon that is AI, we couple a theoretical framework with empirical models to uncover some predictive hypotheses and association effects. More specifically, we investigate whether bilateral trade flows and the number of exporting firms are affected by the use of AI technologies in the European Union between 2021 and 2023.

We unveil through two linear regressions, that one out of our three hypotheses holds. Namely, we find that the use of AI technologies is associated with a decrease in the volume of bilateral trade flows for a country pair. Moreover, still contrary to our expectations, an increase in AI usage is associated with a less negative impact of non-tariff barriers on bilateral trade flows. Finally, we find that an increase in ICT equipment, proxying for AI, is associated with an increase in the number of exporting firms in a country.

As a result, in light of previous research and our findings, AI technologies appear to have both a positive and a negative impact on international trade flows. Therefore, we advise to cater policies regarding AI to the type of effect desired. For instance, echoing to the French farmers in the introduction, our framework does not provide the proofs to suggesting that AI could improve their situation and fill their demands regarding the control of illegally traded products. However, we could suggest the promotion of AI for countries with a considerable number of SMEs looking for help to make their first steps in the export market. Finally, we remind that our contribution to this topic focuses on providing a predictive framework and associative effects rather than causal inferences. We thus advise caution when interpreting the results and we hope that our study might be an incentive for further research on this topic which will affect the global future of trade.

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10. Appendix

10.1 Residuals

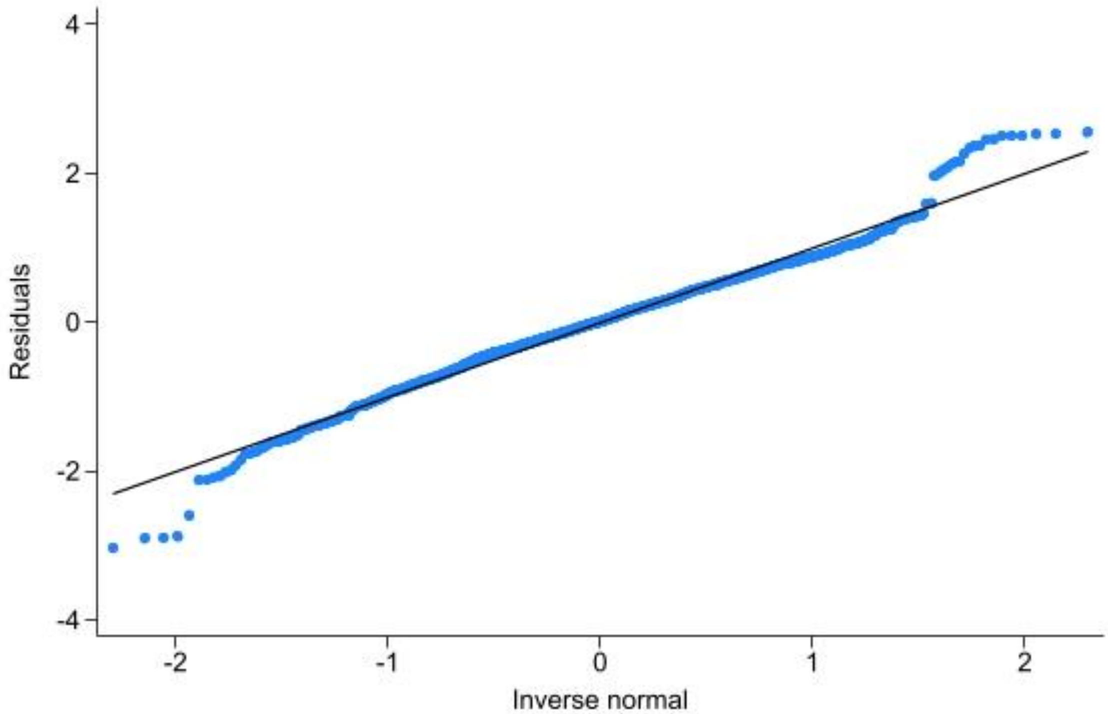

Figure 1: Residuals Q-Q plot for bilateral trade flow in equation (5)

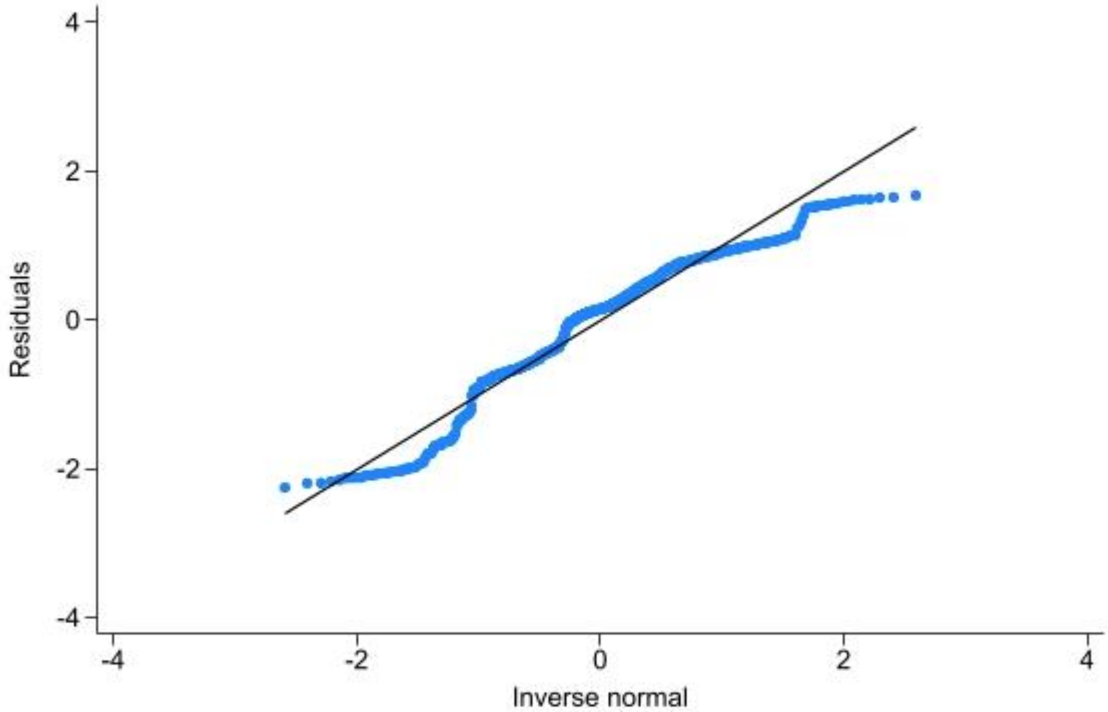

Figure 2: Residuals Q-Q plot for number for exporting firms in equation (6)

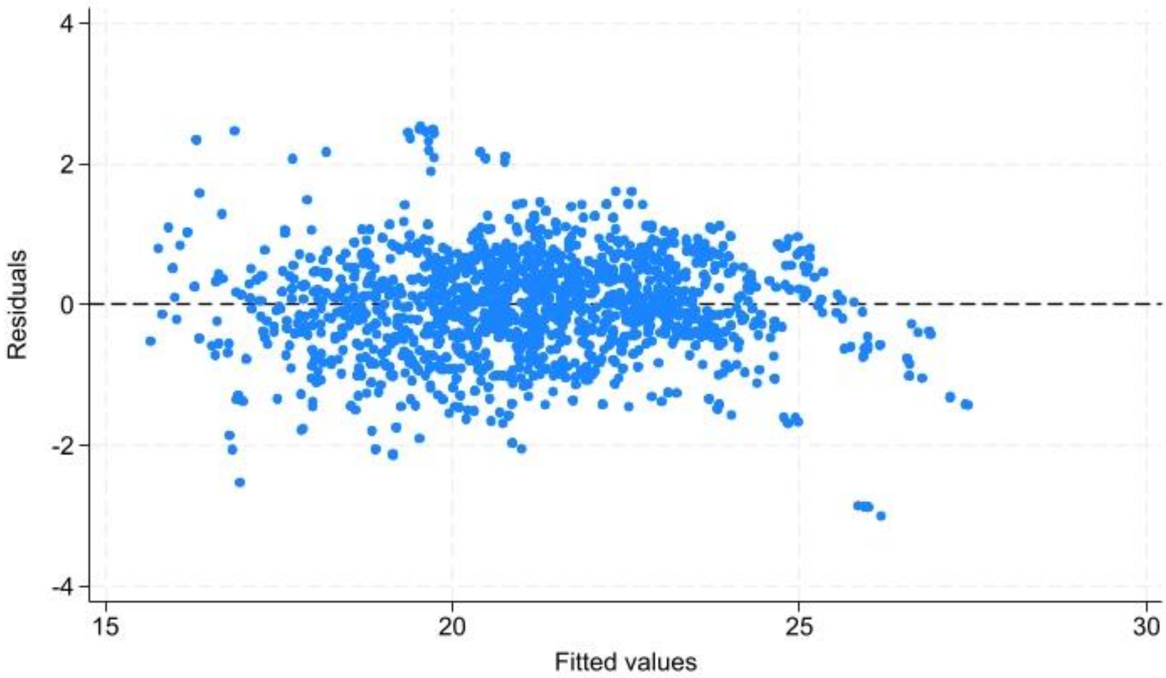

Figure 3: Residuals against Fitted values plot for bilateral trade flow in equation (5)

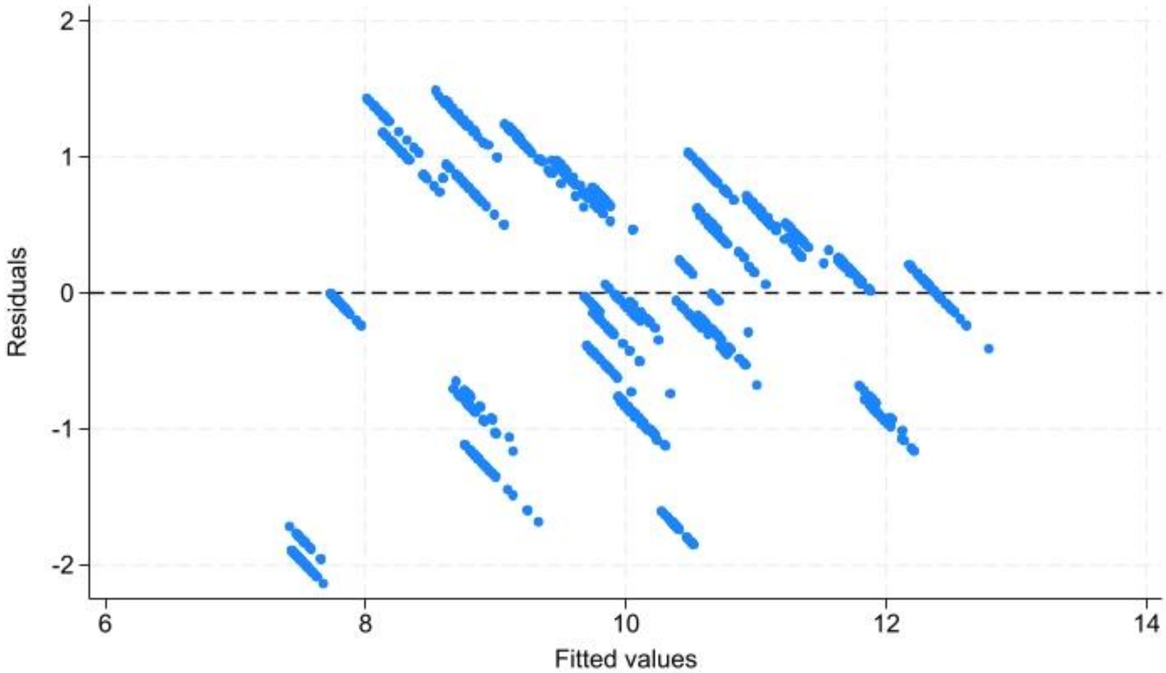

Figure 4: Residuals against Fitted values plot for exporting firms in equation (6)

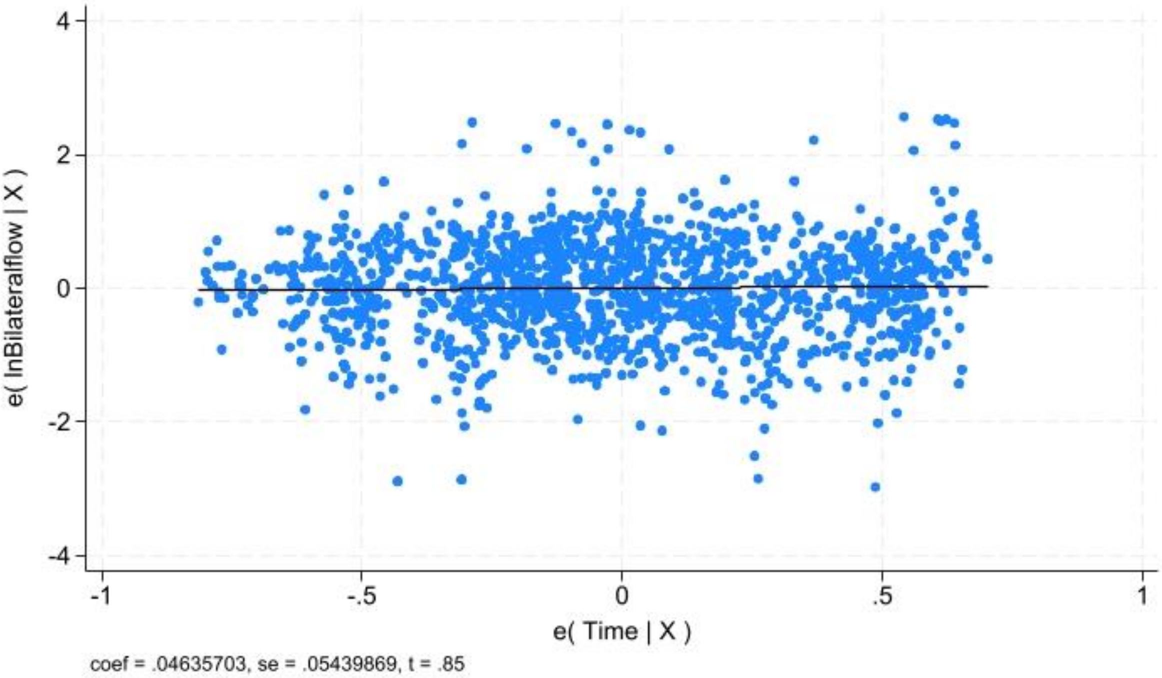

Figure 5: Residuals against time plot for bilateral trade flow in equation (5)

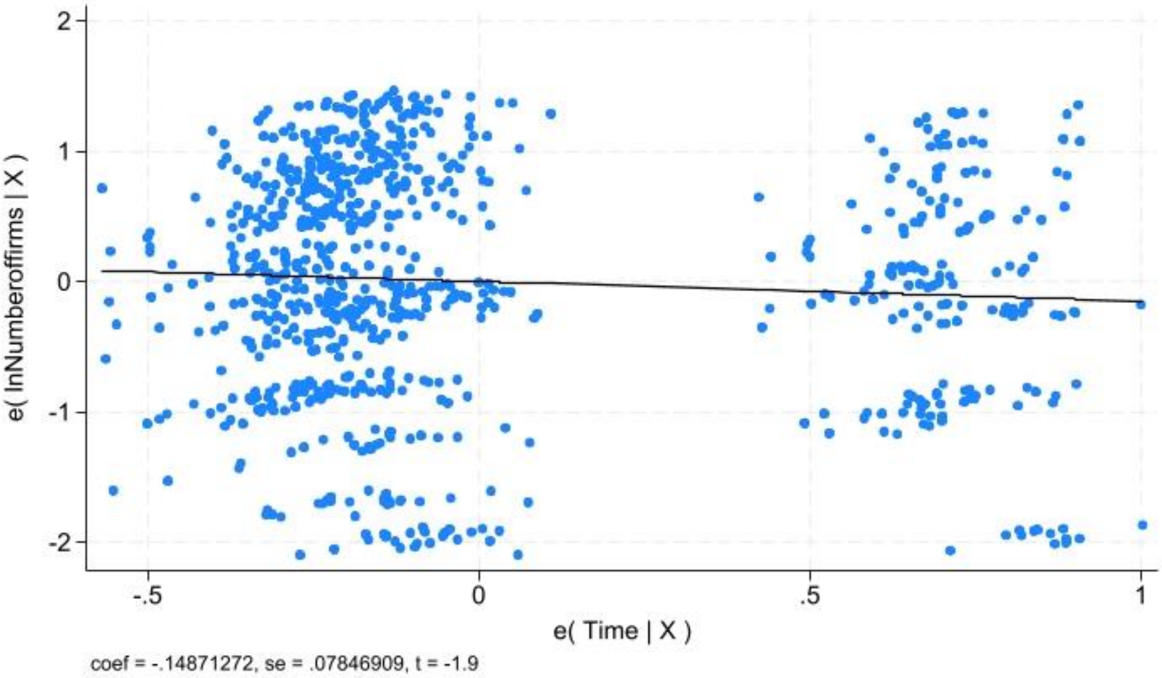

Figure 6: Residuals against time plot for exporting firms in equation (6)

10.2 Additional Resources

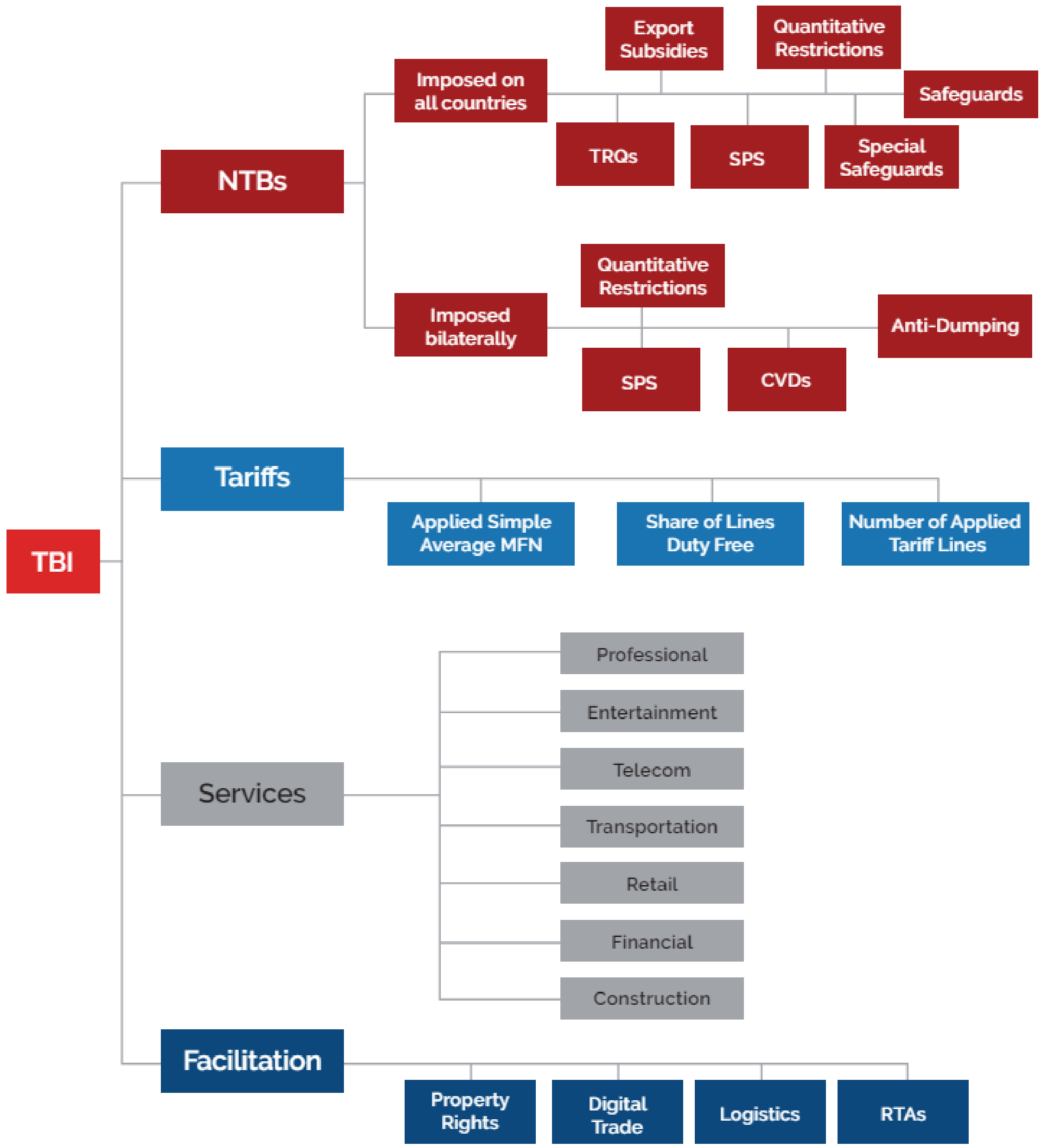

Figure 7: International Trade Barrier Index 2023 composition. Full report page 31

Table 3: Types of AI technologies used in AI Source and AI Partner

Acronym	AI Technology
TTM	Performing analysis of written language
TSR	Converting spoken language into machine-readable format
TNLG	Generating written or spoken language
TIR	Identifying objects or persons based on images
TML	Machine learning (e.g. deep learning)
TPA	Automating different workflows or assisting in decision making
TAR	Enabling physical movement of machines via autonomous decisions based on observation of surroundings

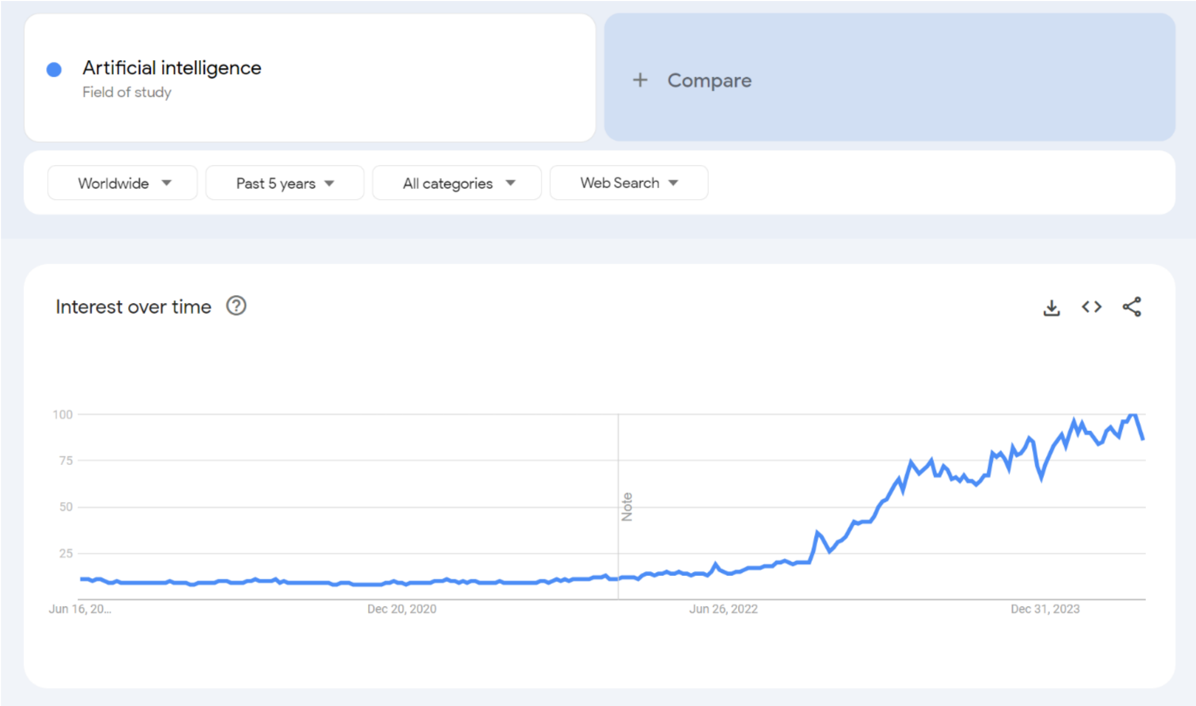

Figure 8: Google trends graph for the term “Artificial Intelligence”